Z-CONCEPTS

CECL: YOU'RE GOING TO NEED A BETTER ALM MODEL

The new Allowance for Loan and Lease Losses standard (called CECL) reminds me of the scene from *Jaws*, where, after first trying to capture the monstrous shark, Chief Brody (Roy Scheider) tells Quint (Robert Shaw), "You're going to need a bigger boat." Well, CECL means bankers are going to need a bigger (i.e., better) ALM model.

Current Expected Credit Losses (CECL) is the Financial Accounting Standards Board's (FASB) new accounting standard for the recognition and measurement of credit losses for loans and debt securities. This standard is moving from an "incurred loss" model to an "expected loss" model. The "incurred loss" model is basically looking at historical defaults rates for one or more classes of loans and leases. Here, if a bank's historical loss rate is 3%, for example, then the bank's allowance account would be set to 3% of the outstanding loan balance. This method has no consideration of whether the bank's loan portfolio is looking to improve or deteriorate in the future. The new standard requires banks to look at expected losses over the life of the loan. These expected losses may be lower or higher than historical losses rates given the prevailing economic forecasts that are expected to exist over the life of the loans.

This may seem like a daunting task: forecasting defaults over the life of a loan which may extend many years into the future. However, if you have a good ALM model, it should already incorporate everything needed to comply with CECL (see *Steps to Satisfy the CECL Standard*, right), such as prepayments and interest rates based on various economic factors, etc. As you will see through the examples provided in this article, if your ALM model doesn't have the necessary functionality, you will need to upgrade.

In order to forecast defaults over the life of the loan, you will need to first forecast or project balances and coupons for the loan. This means you will need to forecast prepayments. Also, the economic climate expected to exist over the life of the loan needs to be handled, including what interest rates are likely to do in the future. All of these features can easily be handled by a good ALM model with a robust cash flow engine and good scenario analysis.

STEPS TO SATISFY THE CECL STANDARD

1. **Analyze your loan data history to determine drivers of defaults**
2. **Derive a default model of each grouping of loans**
3. **Load loans into your ALM model**
4. **Load default models into your ALM model**
5. **Input the most likely economic and rate forecast into your ALM model**
6. **Projected default adjusted cash flows for each loan or loan group**
7. **Run a report that sums your net defaults over the life of the all the loans**

1. ANALYZE LOAN HISTORY

The first step in meeting CECL is to analyze your loan history, with the goal of determining what factors contribute to your bank's charge-off rates. Ideally, you have individual loan history going back through several economic cycles. Besides balances and rates on the loans, you should have some indicators as to borrower and loan quality like FICO, debt to income (DTI), loan to value (LTV), etc. If you do not have this data, you need to start collecting this information as far back as possible. Analyzing individual loans may be more work than an institution is willing or able to perform. At minimum, a bank should group loans into cohorts by product type and driver buckets. For example, you may group all 30 year fixed-rate residential loans with a FICO band of 675-700.

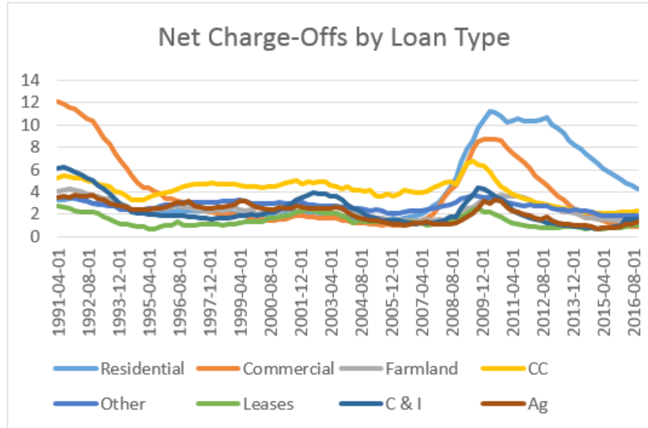

Fig.1: Net Charge-offs by Loan Type

Figure 1 shows net charge-offs by product type for the period 1991 through 2016Q3. Notice all loans and lease experienced large defaults during the economic problems of 2009 and 2010.

2. DERIVE DEFAULT MODEL FOR EACH LOAN GROUP

Once you have identified all your loan cohorts, determine which factors drive defaults. Ideally, these will be a mix of the both internal (loan and borrow specific) and external (economic) factors.

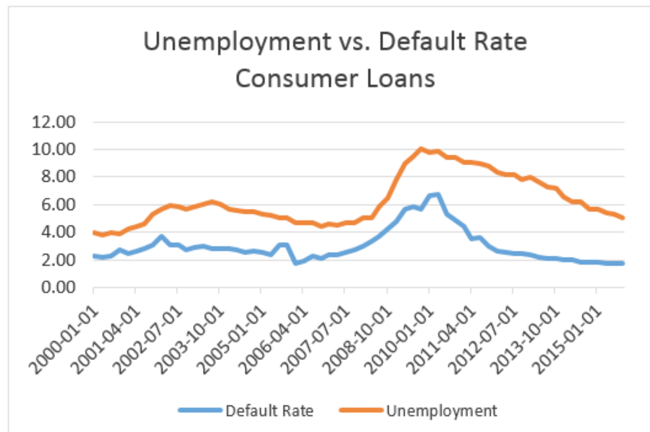

Fig.2: U.S. Treasury Unemployment Rate vs Default Rate Consumer Loans

Figure 2 shows a graph of the U.S. Unemployment Rate and the net charge-offs for consumer loans. Notice how the default rate seems to follow the unemployment rates. When unemployment is low, the default rate is low. Conversely, when unemployment is high, the default rates turn up. This make sense. When people are employed and are making money, they make their mortgage payments. When the economy falters, companies lay off workers and people are less able to make loan payments.

There are many types of statistical models (sub-models) that can be used to model defaults. The more common ones are vectors of probability of defaults (PD), loss given defaults (LGD), migration matrices and regression. There are also third-party models bankers can use.

It is important to note different types of loans may end up using different types of default sub-models. Depending on the data available, not all loan types may yield robust regression equations. Bankers may have to use a mix of different default sub-models.

Using the regression capability in Excel, we were able to derive the following linear equation to forecast defaults for those consumer loans.

*Net default rate = 0.08 + 0.462 * Unemployment rate*
R squared is 47%

The R squared measures the explanatory power of the model. 47% is a pretty good fit.

3. LOAD LOANS IN ALM MODEL

This step should be one you are already performing during you regular IRR and ALM modeling exercises. Here, your loan extracts are mapped and transformed via ETL tools so that individual loans and associated variables are loaded into a database that works with your ALM model. For CECL, you may now need to load additional variables that impact defaults like FICO, DTI, LTV, etc.

4. LOAD DEFAULT MODEL IN ALM MODEL

You may not currently be forecasting defaults as part of your ALM simulations; however, in order to comply with CECL, your ALM model will need to be capable of loading different types of defaults sub-models. These models will need to be attached to individual loans or to loan cohorts if you model at a summarized level.

5. LOAD ECONOMIC AND RATE FORECASTS INTO ALM MODEL

The final step in loading up an ALM model to forecast CECL will be to input your bank's forecast for rates and economic drivers that are needed to feed the default models. As we all know, forecasting is rarely accurate, but bankers should have a reasonable idea of where the economy and the default drivers are headed.

If your bank does not have a forecast, a good source for a consensus economic forecast is to use the baseline forecast from the Federal Reserve, which is used for Dodd-Frank Stress Tests (see Figure 3). The banker would load those variables and rates needed to model the cash flows, prepayments and defaults for each loan or cohort of loans.

Table 1A.—*continued*

Date	Real GDP growth	Nominal GDP growth	Real disposable income growth	Nominal disposable income growth	Unemployment rate	CPI inflation rate	3-month Treasury rate	5-year Treasury yield	10-year Treasury yield	BBB corporate yield	Mortgage rate	Prime rate	Level			
													Dow Jones Total Stock Market Index	House Price Index	Commercial Real Estate Price Index	Market Volatility Index
Q4 2010	2.5	4.7	2.8	5.0	9.5	3.3	0.1	1.5	3.0	5.0	4.5	3.3	13,131.5	140.3	173.0	23.5
Q1 2011	-1.5	0.2	5.0	8.2	9.1	4.3	0.1	2.1	3.5	5.4	4.9	3.3	13,908.5	138.5	180.0	29.4
Q2 2011	2.9	6.0	-0.6	3.5	9.1	4.7	0.0	1.8	3.3	5.1	4.6	3.3	13,843.5	137.7	177.0	22.7
Q3 2011	0.8	3.3	2.1	4.3	9.0	2.6	0.0	1.1	2.5	4.9	4.2	3.3	11,676.5	137.7	177.0	48.0
Q4 2011	4.6	5.2	0.2	1.6	8.6	1.7	0.0	1.0	2.1	5.0	4.0	3.3	13,019.3	137.6	188.0	45.5
Q1 2012	2.7	4.9	6.7	9.2	8.3	2.2	0.1	0.9	2.1	4.7	3.9	3.3	14,627.5	139.6	188.0	23.0
Q2 2012	1.9	3.8	3.1	4.4	8.2	1.0	0.1	0.8	1.8	4.5	3.8	3.3	14,100.2	142.8	189.0	26.7
Q3 2012	0.5	2.7	-0.2	1.1	8.0	1.8	0.1	0.7	1.6	4.2	3.5	3.3	14,894.7	145.7	197.0	20.5
Q4 2012	0.1	1.7	10.9	13.3	7.8	2.6	0.1	0.7	1.7	3.9	3.4	3.3	14,834.9	149.3	198.0	22.7
Q1 2013	1.9	3.6	-15.9	-14.7	7.7	1.4	0.1	0.8	1.9	4.0	3.5	3.3	16,396.2	153.8	202.0	19.0
Q2 2013	1.1	2.1	2.7	3.1	7.5	-0.1	0.1	0.9	2.0	4.1	3.7	3.3	16,771.3	158.8	213.0	20.5
Q3 2013	3.0	4.9	2.2	3.9	7.2	2.3	0.0	1.5	2.7	4.9	4.4	3.3	17,718.3	163.0	224.0	17.0
Q4 2013	3.8	5.6	0.6	2.0	7.0	1.4	0.1	1.4	2.8	4.8	4.3	3.3	19,413.2	166.3	229.0	20.3
Q1 2014	-0.9	0.6	4.0	5.6	6.7	2.1	0.0	1.6	2.8	4.6	4.4	3.3	19,711.2	169.3	230.0	21.4
Q2 2014	4.6	6.9	3.0	5.2	6.2	2.4	0.0	1.7	2.7	4.3	4.2	3.3	20,568.7	170.7	239.0	17.0
Q3 2014	4.3	6.0	2.7	3.9	6.1	1.2	0.0	1.7	2.5	4.2	4.1	3.3	20,458.8	172.5	245.0	17.0
Q4 2014	2.1	2.2	4.7	4.2	5.7	-0.9	0.0	1.6	2.3	4.2	3.9	3.3	21,424.6	174.5	252.0	26.3
Q1 2015	0.6	0.8	3.9	1.9	5.6	-3.1	0.0	1.5	2.0	4.0	3.7	3.3	21,707.6	177.3	260.0	22.4
Q2 2015	3.9	6.1	2.6	4.9	5.4	3.0	0.0	1.5	2.2	4.2	3.8	3.3	21,630.9	179.4	264.0	18.9
Q3 2015	2.0	3.3	3.8	5.1	5.2	1.6	0.0	1.6	2.3	4.5	3.9	3.3	19,959.3	181.7	270.0	40.7
Q4 2015	1.9	1.9	3.5	3.8	5.0	0.2	0.1	1.6	2.2	4.6	3.9	3.3	21,100.9	183.1	273.4	24.4
Q1 2016	2.5	4.0	2.8	3.5	4.9	1.2	0.4	1.8	2.4	4.5	4.1	3.6	21,336.7	184.0	276.8	24.8
Q2 2016	2.6	4.0	2.5	4.3	4.8	2.2	0.6	2.0	2.6	4.7	4.2	3.8	21,578.3	185.2	280.3	24.6
Q3 2016	2.6	4.3	2.6	4.5	4.7	2.3	0.9	2.2	2.7	4.8	4.3	4.0	21,834.8	186.3	283.8	23.2
Q4 2016	2.5	4.3	2.6	4.6	4.6	2.3	1.0	2.4	2.9	4.9	4.5	4.1	22,093.2	187.5	287.4	22.7
Q1 2017	2.4	4.1	2.8	4.8	4.6	2.2	1.3	2.6	3.0	5.0	4.6	4.4	22,347.4	188.7	291.0	22.5
Q2 2017	2.5	4.6	2.6	4.8	4.6	2.4	1.5	2.7	3.1	5.1	4.7	4.6	22,626.3	189.9	294.7	22.0
Q3 2017	2.3	4.6	2.5	4.7	4.5	2.4	1.9	2.9	3.3	5.2	4.9	5.0	22,908.0	191.1	298.4	21.4
Q4 2017	2.3	4.4	2.6	4.7	4.5	2.3	2.2	3.0	3.4	5.3	5.0	5.3	23,183.2	192.2	302.1	21.7
Q1 2018	2.6	4.3	2.9	4.7	4.5	2.0	2.4	3.1	3.5	5.4	5.2	5.5	23,458.2	193.7	304.4	21.4
Q2 2018	2.4	4.2	2.6	4.6	4.6	2.1	2.6	3.2	3.6	5.5	5.3	5.7	23,733.2	195.2	306.7	21.5
Q3 2018	2.3	4.2	2.6	4.5	4.6	2.1	2.7	3.2	3.7	5.6	5.4	5.8	24,008.9	196.6	309.0	21.4
Q4 2018	2.3	4.1	2.5	4.5	4.7	2.1	2.8	3.3	3.8	5.6	5.5	5.9	24,285.1	198.1	311.4	21.5
Q1 2019	2.1	4.0	2.4	4.3	4.7	2.1	2.8	3.4	3.8	5.6	5.5	5.9	24,555.9	199.6	313.7	21.4

Fig.3: Sample of Federal Reserve Baseline Forecast use for Dodd-Frank Stress Test

Figure 4 shows the forecast for unemployment rates in 2017 and 2018 are in the mid 4%. Therefore, using the regression equation from Figure 3, we know our default rate will be around 2.2%.

	A	B	C
1	Period	Unemp	Defaults
2	201701	4.6	2.21
3	201702	4.6	2.21
4	201703	4.5	2.16
5	201704	4.5	2.16
6	201801	4.5	2.16
7	201802	4.6	2.21
8	201803	4.6	2.21
9	201804	4.7	2.25
10	201901	4.7	2.25

Fig.4: 2017/2018 Unemployment Rate Forecast Default Rate

Note: The Dodd-Frank Stress Test scenarios only go 9 quarters from the current year-end. Since the CECL standard needs to forecast defaults over the life of the loan, users will need a forecast beyond the nine quarters. The standard says defaults forecasts over 24 months are unsupportable and therefore should revert back to using the historical default rate.

6. PROJECT DEFAULT ADJUSTED CASH FLOWS

The last step in the process is to project default adjusted cash flows for each loan or cohort over the life of the loan. As mentioned above, these cash flows should include balances, loan coupons (including any adjustable loan resets), prepayments and now the projected default rates from whichever sub-model is used. You cannot get proper default amounts if you don't project balances, coupon rates and prepayments accurately. This is because, at the outset, banks will not know how long the loan will be outstanding. Only by using a good ALM model setup as described above will the bankers know the true defaults over the life of the loans.

7. GETTING THE ALLOWANCE

Once you have default adjusted cash flows you sum up the present value of the net defaults by product type or product cohorts over the life of the loan. The allowance is simple: the sum of all the defaults off all the loans/cohorts over the ALM horizon period, which should extend to after the last loan has ended due to maturity, prepayments, or defaults. Note: the net default rates should be discounted by the loan/cohort coupon rate to get the present value of the net defaults.

Note: The standard only requires bankers to forecast defaults on the current book of business. Future originations and purchases of loan and other instruments are not expressly modeled. So, not planning for defaults in replacement business could lead to some bumpy allowance numbers month to month.

GETTING FUTURE LOAN PROVISIONS

The allowance the next month will follow a similar process, but all of the loans are aged one month. Any replacement business must now be modeled. All loans existing at time zero will now be reduced by any scheduled or unscheduled principle payments. Any deterioration of loan quality over the month should now be updated, which will impact the default model forecasts.

Provision(1) = ALL(0) – Actual Losses + Actual Recoveries – ALL(1)

MOVING FORWARD

These examples demonstrate how the new allowance for loan and lease losses are full of assumptions. We are no longer estimating credit losses back to the origination date. With CECL, we're now looking at the life of the loan. Take a good look at the steps outlined in this article and think about how your ALM model works. Is it time for a bigger boat?

Bank management needs to not only have the proper tools to specify the time zero allowance but also needs to be aware of forward CECL and the sensitivity of CECL to changing assumptions. In our next article we'll explore these concepts.

About the Author

As one of the co-founders of ZM Financial Systems (ZMFS), Frank "Butch" Miner is directly responsible for the management, growth and success of business operations, overseeing all day-to-day operations in addition to leading corporate strategic initiatives. Miner and ZMFS co-founder Dai Zhao had a vision: to develop, implement and support a truly integrated risk analytics product that could be used by multiple departments inside a financial institution yet run off the same analytic engine and database. Starting off on their own, Zhao's quantitative analytics and financial modeling experience, combined with Miner's portfolio management capital markets and risk management knowledge, led to the formation of ZM Financial Systems.

Prior to founding ZMFS, Miner served as Managing Director, IPS-Sendero; Senior Vice President, Pinehurst Analytics; and Portfolio Manager, Smith Breeden Associates. He received his B.S. in Finance from Florida Southern College, and his Masters in both Accounting and Finance from the University of Iowa, Henry B. Tippie College of Business.

About ZM Financial Systems

ZM Financial Systems brings practical solutions to complex financial problems, offering complete solutions in securities and fixed-income analytics, credit-adjusted ALM, liquidity, risk management, budgeting and funds transfer pricing. We also offer large bank solutions to meet the evolving regulatory risk reporting requirements. With 1,500 institutions depending on ZMFS products/analytics to identify, measure and monitor risk and value in their balance sheets, we are one of the fastest growing financial software companies in the U.S.

Founded in 2003, ZMFS is a privately-held corporation headquartered in Cary, N.C. In addition to the 25 percent of our staff who have PhD's in the advanced quantitative field, our development and product support teams all have experience in the finance arena. Because our teams continuously collaborate, we can quickly navigate complex solutions to complete client-requested enhancements in days or weeks, versus months or years.

Delivering state-of-the-art risk/reward analysis tools, such as ZMdesk™, OnlineALM.com™ and OnlineBondSwap.com™, our clients are empowered to uncover hidden risk while maximizing performance; test lending, investment and funding strategies; and respond to various regulatory requirements while efficiently delivering actionable information.

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